Coordinated Expansion Planning Problem considering Wind Farms, Energy Storage Systems and Demand Response

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Abstract- During the recent years, the power system has entered a new technological era. The trends associated with increased commitment to wind farms (WFs) and energy storage systems (ESSs) as well demand side flexibility require disruptive changes in the existing power system structures and procedures. Being at the heart of a paradigm shift from passive users of the grid to active prosumers, storage owners and demand responsive actors, this paper expresses a flexible coordinated power system expansion planning (CPSEP) while considering local WFs, ESSs and incentive-based demand response programs (DRPs). This model minimizes the summation of the expansion planning, operation and reliability costs while taking the network model based on AC optimal power flow constraints, and the reliability and flexibility considerations into account. The proposed framework is firstly formulated by mixed integer non-linear programming (MINLP), then to have a well-handed optimization model it is converted to mixed-integer linear programming (MILP). Additionally, the uncertainties of load, energy price, maximum WF generation and availability/unavailability of the network equipment are included in the proposed model where the first three parameters are modeled based on the bounded uncertainty-based robust optimization (BURO), and the scenario-based stochastic programming (SBSP) is used to model the last uncertain parameter. Finally, the proposed method is examined on several test networks to assess the performance of the proposed framework for flexi-reliable transmission network operation and planning.

Keywords: Expansion planning; uncertainty; robust optimization; demand response programs; energy storage systems.

List of Symbols

Indices

g, w, s, l	Indices of Generating Units (GUs), Wind Farms (WFs), Energy Storage Systems (ESSs) and load, respectively
i, j, k	Indices of bus, bus, scenario, respectively
m, n	Indices of linearized segments for non-linear terms of AC power flow equations
t, h	Indices of years and hours, respectively

Parameters

A_G, A_L, A_W, A_D, A_{ESS}	Incidence matrix between bus and generation, bus and line, bus and wind farm, bus and load, bus and ESS, respectively.
C^G, C^W, C^L, C^{ESS}	Capital cost of GUs, WFs, transmission line, and ESSs in M$.
CF	Coincidence factor
$\underline{E}/\overline{E}$	Min/max stored energy in ESS in per unit (p.u.)
g/b	Line conductance and susceptance in p.u.
P^D/Q^D	Active/reactive load in p.u.
$\underline{P}^G/\overline{P}^G$	min/max active power of GU in p.u.
$\overline{P}^W/\overline{P}^{ESS}$	Max active power of WF/ESS system in p.u.
$\underline{Q}^G/\overline{Q}^G$	min/max reactive power of GUs in p.u.
$\overline{S}^L$	Capacity of transmission line in p.u.
$\underline{V}/\overline{V}$	min/max of voltage in p.u.
VOLL	Value of lost load in $/MWh
λ/ρ	Operation price of GUs/energy price in $/MWh
γ	Percentage of load participation in the demand response
$\Delta\alpha$	Deviation of angle in radian
π	Probability of scenarios
η_{ch}/η_{dch}	Charging/discharging efficiency of ESSs

Variables

C_p, C_o, C_r	Cost of expansion, operation and reliability in M$
E	Stored energy in ESSs in p.u.
EENS	Expected energy not supplied in p.u.
P^{ch}/P^{dch}	Active power charging/discharging for ESS in p.u.

P^{DR}	Active power of demand response programs (DRPs) in p.u.
P^{L}/Q^{L}	Active/reactive power flow of transmission lines in p.u.
P^{LNS}	Active load not supplied in p.u.
P^{G}/P^{W}	Active power of GUs /WFs in p.u.
Q^{G}	Reactive power generation for GU in p.u.
s^{ch}/s^{dch}	Binary variable for charging/discharging operation modes of ESS
SF	System flexibility [without unit]
U^{DR}/D^{DR}	Upward/downward flexibility for DRP in p.u.
U^{ESS}/D^{ESS}	Upward/downward flexibility for ESS in p.u.
U^{G}/D^{G}	Upward/downward flexibility for GU in p.u.
V/δ	Voltage magnitude (p.u.)/voltage angle (rad)
$x^{G}, x^{L}, x^{W}, x^{ESS}$	Binary variables indicating the construction status of GUs, transmission lines, WFs, and ESSs, respectively
φ, ψ	Auxiliary functions

1. Introduction

1.1 Motivation and Approach

The coordinated power system expansion planning (CPSEP) problem is one of important power system planning problems to supply the load growth in the future years. This method couples the generation and transmission expansion planning (G&TEP) and optimal scheduling of renewable energy sources (RESs) such as wind farms (WFs) and energy storage systems (ESSs). Also, this problem can consider different types of demand response programs (DRPs) [1]. Noted that this problem is kind of a complex non-linear optimization problem, where its solution method is complex, and it suffers from the high computational burden while the global optimal solution cannot be guaranteed [2]. Moreover, this strategy includes different uncertain parameters such as load, wind energy generation, energy price, and the forced outage rates (FORs) of the network equipment. Therefore, ignoring the forecasted error of different uncertain parameters or using an inappropriate method to model these parameters may lead to critical conditions and error in power systems operation and planning in the future years [3]. Hence, the CPSEP problem needs a suitable model based on its objective functions and constraints to obtain a robust and optimal solution.

1.2 Literature Review

There are different models for power system planning. For instance, in [4], a bi-level optimization model has been proposed for G&TEP based on game theory, where the upper-level models the transmission expansion planning (TEP) and the lower-level problem refers to generation expansion planning (GEP) in the restructured environment of power systems. In [5], a stochastic G&TEP model implemented on the power networks while considering the natural disaster impacts such as earthquake.

Also, a probabilistic method is used in [6] to model the uncertain parameters in the reliable G&TEP while presenting linear formulations. The multi-objective G&TEP strategy to minimize the expansion planning cost and the effects of environmental pollution is proposed in [7]. Also, in [8], the ESS and transmission switching of the grid-connected wind generation have been embedded in TEP.

In addition, the authors of [9-11] have studied the G&TEP model based on the AC power flow equation, where its solution method is based on the conventional evolutionary algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), etc. Also, in [12-14], different models of power system planning according to DC power flow equations are introduced to obtain linear formulation for these models. The other models of the power system planning are presented in [15-19]; the authors of [15] have modeled the impacts of DR and long-run incremental cost (LRIC) based on the pricing signals in the G&TEP formulation. Also, the TEP model based on branch-and-cut Benders decomposition (BCBD) algorithm is expressed in [16] to obtain high calculation speed. In [17], a tri-level approximation algorithm is used to model the probability of TEP based on the curtailment of wind power generation. Finally, the stochastic bi-level model of TEP is studied respectively in [18] and [19] to consider the uncertainty of different equipment. To summarize the available literature in the area, the taxonomy of recent research works is addressed in Table 1.

Table 1: Taxonomy of recent research works

Ref.	Power flow model	Flexibility modeling	Uncertainty modeling
[4-7]	DC	No	Stochastic
[8]	DC	No	Robust
[9-11]	AC	No	Stochastic
[12-19]	DC	No	Stochastic
This paper	**Linearized AC**	**Yes**	**Hybrid stochastic-robust**

1.3 Research Gaps

Briefly, the main research gaps in the area according to the above-mentioned research works and Table 1 can be summarized as follows:

- Much research consider G&TEP model based on DC power flow equations to adapt linear formulations for this model. While the reactive power and power losses of the power system operation are ignored in these models, they result in significant errors in the real operation of the power systems. For example, it is possible that a transmission line or a generating unit (GU) is not considered to be constructed in the network according to DC-based CPSEP model, but the solution of CPSEP model may propose to construct some GUs or transmission lines. Also, the non-linear modeling of the G&TEP solved by evolutionary algorithms are not reliable solutions and it suffers from a high computational burden.
- Also, to the best of authors' knowledge, the system flexibility as an important index in the current power system planning studies is not considered so far. Noted that the flexibility term defined as "*the modification of generation injection and/or consumption patterns in reaction to an external price or activation signal in order to provide a service within the electrical system.*" [20-22].

- Significant shares of the available research in the area implement the stochastic programming (SP) to model the uncertainty sources of the power system planning problem. However, the SP needs a high number of scenarios and complete knowledge about the probability density function (PDF) of uncertain parameters to achieve a reliable solution. Noted that in the scenario-based stochastic programming (SBSP), the scenario reduction method can decrease the high number of generated scenarios to have limited numbers of scenario samples. However, in this approach, significant number of scenarios are needed to obtain a reliable solution. For example, considering three scenarios for each uncertainty of active and reactive load, energy price, RES power, and availability/unavailability of the network equipment in the proposed CPSEP, the proposed problem needs 324 (=3^5) scenarios.

1.4 Contributions

To cope with the above research gaps, this paper presents a reliable and flexible CPSEP strategy, as shown in Fig. 1, to optimize operation and planning of the transmission lines, GUs, WFs, ESSs and incentive based DRPs in power systems. Hence, the SP modeling of the proposed strategy is formulated firstly, where it minimizes the summation of operation, expansion planning and reliability costs subject to AC power flow equations, ESS, WFs and DRP constraints, system operation limits, reliability and the flexibility constraints. Noted that this original model is as mixed integer non-linear programming (MINLP) form that generally reveals a locally optimal solution at the high computational burden. Therefore, this MINLP model is converted to mixed integer linear programming (MILP) to achieve the global optimal solution with low computational burden and error with respect to the original model. In addition, to obtain a robust and secure optimization for the proposed CPSEP formulation, this paper implements the hybrid stochastic/robust optimization (HSRO) to model the uncertainty of load, energy price and maximum WF active power based on the bounded uncertainty-based robust optimization (BURO), and uncertainty of the availability/unavailability of the network equipment is modeled according to the SBSP using Monte Carlo Simulation (MCS).

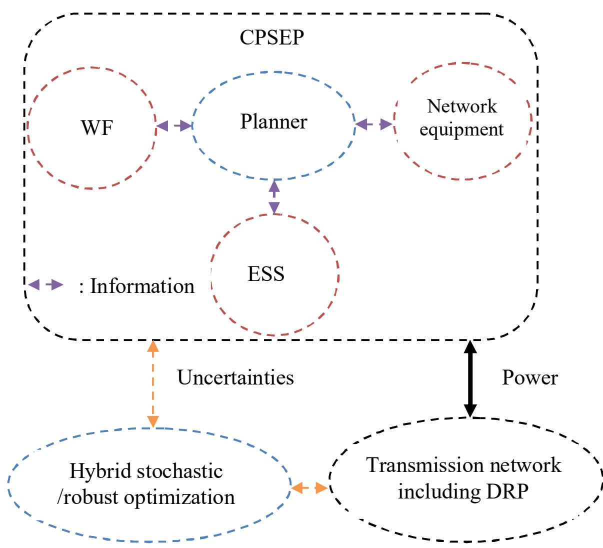

Fig. 1. The proposed CPSEP framework.

Accordingly, to the best of authors' knowledge, the main contributions of this paper can be summarized as follows:

- Developing non-linear and linear models of the CPSEP problem while considering the reliability and flexibility of the system.
- Modeling the uncertainty using hybrid stochastic/robust optimization to obtain a robust and secure optimal solutions.

1.5 Paper Organization

The rest of this paper is organized as follows: In Section 2, the MINLP and MILP stochastic models of CPSEP are expressed. Section 3 models the uncertainty in the CPSEP by means of hybrid stochastic/robust optimization. Sections 4 and 5 present the simulation results and conclusions, respectively.

2. Original Problem Model

In this section, the proposed SP is presented for the CPSEP problem to minimize the sum of expansion, operation and reliability costs subject to power system operation and planning constraints.

2.1 Non-linear model

The original non-linear model of the proposed CPSEP based on the following assumptions is developed in (1)-(30):

- Wind farms are considered as renewable energy sources in this model.
- ESSs, non-renewable GUs, and DRPs are flexibility sources in transmission network.
- Disconnection of GUs, WFs, ESS, load, and transmission lines from network are modeled by N – 1 contingency criteria,
- DRP formulation is based on incentive-based model that is depended to energy price.

$$\min \ C_p + C_{op} + C_r \tag{1}$$

Subject to:

$$C_p = \sum_g C_g^G \cdot x_g^G + \sum_w C_w^W \cdot x_w^W + \sum_{i,j} C_{i,j}^L \cdot \frac{x_{i,j}^L}{2} + \sum_s C_s^{ESS} \cdot x_s^{ESS} \tag{2}$$

$$C_o = \overbrace{\sum_{t,h} CF.365.\left[\sum_g \lambda_g \cdot P_{g,t,h}^G + \sum_s \rho_{t,h} \cdot \left[P_{s,t,h}^{ch} - P_{s,t,h}^{dch}\right] - \sum_l \rho_{y,h} \cdot P_{l,y,h}^{DR}\right]}^{C_o^0} + \sum_k \pi_k \cdot C_o^k(P_{g,t,h,k}^G, P_{s,t,h,k}^{ch}, P_{s,t,h,k}^{dch}, P_{l,t,h,k}^{DR}) \tag{3}$$

$$C_r = VOLL \times \left[\overbrace{\sum_{i,t,h,k} CF \times 365 \times \pi_k \cdot P_{i,t,h,k}^{LNS}}^{EENS}\right] \tag{4}$$

$$\sum_l A_{Di,l} \cdot P_{l,t,h}^D - \sum_g A_{Gi,g} \cdot P_{g,t,h}^G - \sum_s A_{ESS\,i,s} \cdot \left[P_{s,t,h}^{dch} - P_{s,t,h}^{ch}\right] - \sum_w A_{W\,i,w} \cdot P_{w,t,h}^W + \sum_j A_{Li,j} \cdot P_{i,j,t,h}^L - \sum_l A_{Di,l} \cdot P_{l,t,h}^{DR} = 0 \quad \forall i,t,h \tag{5}$$

$$\sum_g A_{Gi,g} \cdot Q_{g,t,h}^G - \sum_j A_{Li,j} \cdot Q_{i,j,t,h}^L = \sum_l A_{Di,l} \cdot Q_{l,t,h}^L \quad \forall i,t,h \tag{6}$$

$$P_{i,j,t,h}^{L}=\left[g_{i,j}\cdot\left(V_{i,t,h}\right)^{2}-V_{i,t,h}\cdot V_{j,t,h}\cdot\overbrace{\left[g_{i,j}\cdot\cos\left(\delta_{i,t,h}-\delta_{j,t,h}\right)+b_{i,j}\cdot\sin\left(\delta_{i,t,h}-\delta_{j,t,h}\right)\right]}^{\Phi_{i,j,t,h}}\right]\cdot x_{i,j}^{L}\quad\forall i,j,t,h\tag{7}$$

$$Q_{i,j,t,h}^{L}=\left[-b_{i,j}\cdot\left(V_{i,t,h}\right)^{2}-V_{i,t,h}\cdot V_{j,t,h}\cdot\overbrace{\left[g_{i,j}\cdot\sin\left(\delta_{i,t,h}-\delta_{j,t,h}\right)-b_{i,j}\cdot\cos\left(\delta_{i,t,h}-\delta_{j,t,h}\right)\right]}^{\Psi_{i,j,t,h}}\right]\cdot x_{i,j}^{L};\quad\forall i,j,t,h\tag{8}$$

$$\sqrt{\left(P_{i,j,t,h}^{L}\right)^{2}+\left(Q_{i,j,t,h}^{L}\right)^{2}}\leq\overline{S}_{i,j}^{L}\quad\forall i,j,t,h\tag{9}$$

$$\underline{V}_{i}\leq V_{i,t,h}\leq\overline{V}_{i}\quad\forall i,t,h\tag{10}$$

$$x_{i,j}^{L}=x_{j,i}^{L}\quad\forall i,j\tag{11}$$

$$x_{g}^{G}\cdot\underline{P}_{g}^{G}\leq P_{g,t,h}^{G}\leq x_{g}^{G}\cdot\overline{P}_{g}^{G}\quad\forall g,t,h\tag{12}$$

$$x_{g}^{G}\cdot\underline{Q}_{g}^{G}\leq Q_{g,t,h}^{G}\leq x_{g}^{G}\cdot\overline{Q}_{g}^{G}\quad\forall g,t,h\tag{13}$$

$$0\leq P_{w,t,h}^{W}\leq x_{w}^{W}\cdot\overline{P}_{w,t,h}^{W}\quad\forall w,t,h\tag{14}$$

$$-\gamma_{l}\cdot P_{l,t,h}^{D}\leq P_{l,t,h}^{DR}\leq\gamma_{l}\cdot P_{l,t,h}^{D}\quad\forall l,t,h\tag{15}$$

$$\sum_{h}P_{l,t,h}^{DR}=0\quad\forall l,t\tag{16}$$

$$0\leq P_{s,t,h}^{ch}\leq s_{s,t,h}^{ch}\cdot\overline{P}_{s}^{ESS}\quad\forall s,t,h\tag{17}$$

$$0\leq P_{s,t,h}^{dch}\leq s_{s,t,h}^{dch}\cdot\overline{P}_{s}^{ESS}\quad\forall s,t,h\tag{18}$$

$$E_{s,t,h}=E_{s,t,h-1}+\eta_{ch}\cdot P_{s,t,h}^{ch}-\frac{1}{\eta_{dch}}\cdot P_{s,t,h}^{dch}\quad\forall s,t,h\tag{19}$$

$$x_{s}^{ESS}\cdot\underline{E}_{s}\leq E_{s,t,h}\leq x_{s}^{ESS}\cdot\overline{E}_{s}\quad\forall s,t,h\tag{20}$$

$$s_{s,t,h}^{ch}+s_{s,t,h}^{dch}\leq x_{s}^{ESS}\quad\forall s,t,h\tag{21}$$

$$P_{i,t,h,k}^{LNS}=\text{Left side of Eq.(5) with indices } k \text{ for all power generations}\tag{22}$$

$$\sum_{g}A_{Gi,g}\cdot Q_{g,t,h,k}^{G}-\sum_{j}A_{Li,j}\cdot Q_{i,j,t,h,k}^{L}=\sum_{l}A_{Di,l}\cdot Q_{l,t,h,k}^{L};\forall i,t,h,k\tag{23}$$

$$0\leq P_{i,t,h,k}^{LNS}\leq\sum_{l}A_{Di,l}\cdot P_{l,t,h,k}^{D}\quad\forall i,t,h,k\tag{24}$$

Constraints (7)-(10) and (12)-(21) for all scenarios; (25)

$$U_{g,t,h,k}^{G}-D_{g,t,h,k}^{G}=P_{g,t,h,k}^{G}-P_{g,t,h}^{G}\quad\forall P_{g,t,h}^{G}\in\arg\left\{(1)-(21)\right\};\forall g,t,h,k\tag{26}$$

$$U_{s,t,h,k}^{ESS}-D_{s,t,h,k}^{ESS}=\left[P_{s,t,h,k}^{dch}-P_{s,t,h,k}^{ch}\right]-\left[P_{s,t,h}^{dch}-P_{s,t,h}^{ch}\right]\quad\forall P_{s,t,h}^{dch},P_{s,t,h}^{ch}\in\arg\left\{(1)-(21)\right\};\forall s,t,h,k\tag{27}$$

$$U_{l,t,h,k}^{DR}-D_{l,t,h,k}^{DR}=P_{l,t,h,k}^{DR}-P_{l,t,h}^{DR}\quad\forall P_{l,t,h}^{DR}\in\arg\left\{(1)-(21)\right\}\quad\forall l,t,h,k\tag{28}$$

$$U^G, D^G, U^{DR}, D^{DR}, U^{ESS}, D^{ESS} \geq 0 \tag{29}$$

$$SF = \sum_{g,t,h,k} \pi_k . \frac{U^G_{g,t,h,k} + D^G_{g,t,h,k}}{\left[\overline{P}^G_g - \underline{P}^G_g\right]} + \sum_{l,t,h,k} \pi_k . \frac{U^{DR}_{l,t,h,k} + D^{DR}_{l,t,h,k}}{2\gamma_l P^D_{l,t,h}} + \sum_{s,t,h,k} \pi_k . \frac{U^{ESS}_{s,t,h,k} + D^{ESS}_{s,t,h,k}}{2\overline{P}^{ESS}_s} \tag{30}$$

The proposed objective function of the CPSEP problem is expressed in (1) including three terms. The first term of (1) refers to annual expansion costs of the transmission lines, GUs, WFs and ESSs as formulated in (2). Eq. (2) includes four terms referring respectively to the annual investment cost of GUs, WFs, transmission lines and ESSs. Each term is equal to the product of annual investment cost and binary variable related to the construction status of the candidate elements. The second term of the objective function (1) presents the annual operation cost mentioned in (3) including the operation cost of GUs, ESSs and DRP in different scenarios. Eq. (3) includes two terms, where the first term refers to summation of the fuel cost of GUs (first term), ESSs and DRP energy costs (second and third terms) in the base case (C^0_o). In the base case, the deterministic condition is considered, i.e., a scenario including forecasted value of uncertainty parameters. The proposed CPSEP model is based on the forecasted value of uncertain parameters and all possible scenarios. Hence, the second term of Eq. (3) refers to expected operation cost of GUs, ESSs and DRP, where operation cost in scenario k is based on the same equation with C^0_o while considering the situation of equipment and realized uncertain parameters of each scenario. Noted that C^k_o is a function of $P^G_{g,t,h,k}$, $P^{dch}_{s,t,h,k}$, $P^{ch}_{s,t,h,k}$ and $P^{DR}_{l,t,h,k}$ in scenario k. Finally, the reliability cost is expressed in the third term of (1) and formulated by (4) with considering blackout cost of network loads that is dependent of the expected energy not supplied (EENS) [6]. Noted that, it is assumed that WFs have unity power factor; hence, the AC optimal power flow constraints, in this case, is formulated as (5)-(11) which are respectively nodal active and reactive power balance, line active and reactive power flow, buses voltage and line capacity limitations as well as logical conditions on the binary variable of lines' investment [2]. The constraints (12) and (13) present the active and reactive power limit of the GUs in the base case, respectively. Also, the WF capacity limit is presented in (14) where it's upper limit ($\overline{P}^W$) depends on the wind speed; hence, it is variable for different times and scenarios [2].

In this paper, the incentive-based model of the DRP is used in the CPSEP formwork where it is formulated as (15) and (16) [23-25], and it is assumed that all loads can participate in the proposed DR scheme. Hence, constraint (15) refers to the DR power limit that is equal to γ percent of the network loads. In the proposed method, the required daily energy of loads should be provided in the 24-hours operation according to (16); therefore, they can shift their consumption from the peak load time to the off-peak load period based on the energy price and cost function of DRP in (3). The equations (17) to (21) refer to ESS operation and planning constraints [8, 26], where they respectively refer to the charging and discharging active power limits of the ESS, stored energy equation and limit in the ESS, and a logical condition for ESS where it prevents the simultaneous operation of charging and discharging modes. Finally, the binary variables x^L, x^G, x^W and x^{ESS} respectively refer to the investment of the transmission line, GUs, WFs and ESSs. Hence, each element can be connected to the network if the related binary variable is equal to 1.

For the calculation of the reliability cost in (4), the nodal active and reactive power balance for all scenarios related to the uncertainty of load, energy price, WF and availability/unavailability of the network equipment are explained in (22) and (23) to obtain active load not supplied ($P_{i,t,h,k}^{LNS}$) that is limited by (24) [6].

Moreover, equations (7)-(10) and (12)-(21) are repeated for all scenarios as shown in (25), wherein $P_{l,t,h,k}^{DR}$, $E_{s,t,h,k}$, $P_{g,t,h,k}^{G}$, $Q_{g,t,h,k}^{G}$, $P_{w,t,h,k}^{W}$, $P_{i,j,t,h,k}^{L}$, $Q_{i,j,t,h,k}^{L}$, $P_{s,t,h,k}^{ch}$, $P_{s,t,h,k}^{dch}$, $s_{s,t,h,k}^{ch}$, $s_{s,t,h,k}^{dch}$, $V_{i,t,h,k}$ and $\delta_{i,t,h,k}$, are replaced respectively with $P_{l,t,h}^{DR}$, $E_{s,t,h}$, $P_{g,t,h}^{G}$, $Q_{g,t,h}^{G}$, $P_{w,t,h}^{W}$, $P_{i,j,t,h}^{L}$, $Q_{i,j,t,h}^{L}$, $P_{s,t,h}^{ch}$, $P_{s,t,h}^{dch}$, $s_{s,t,h}^{ch}$, $s_{s,t,h}^{dch}$, $V_{i,t,h}$ and $\delta_{i,t,h}$.

It is noted that the numerical indices are considered to investigate network flexibility [27]. Hence, the upward and downward flexibility capacity of the flexible sources (FSs) such as GUs, ESSs and DRP are calculated by (26)-(28), respectively. Accordingly, the FS will be provided with the upward flexibility in scenario *k* if the difference between its power in the scenario *k* and the base case is positive; otherwise, it will provide downward flexibility. Noted that the flexibility capacity is a positive variable based on (30). Also, system flexibility (SF) is calculated according to (31) while the SF is equal to the summation of the rate of the total FS flexibility to FS power range [27].

2.2 Linear model

The proposed original CPSEP model is a non-convex MINLP model due to the presence of product of binary and continuous variables and non-linear equations (7)-(9) as well as non-convex constraints (7)-(8) [28-30]. Accordingly, as mentioned before, this model cannot achieve the global optimal solution due to the non-convex formulation. In addition, it suffers from high computational burden due to the large-scale size of the problem and non-linear formulations [28-30]. Accordingly, the proposed MINLP is converted to the MILP model based on some linearization techniques to obtain a more accurate globally optimal solution with a low computational burden based on the following assumptions:

- The voltage angle difference between adjacent buses is in the range of [-π/6 π/6] in the transmission networks [2] to ensure stability in this system,
- The range of voltage deviations from 1 p.u. is [0.95 1.05] p.u.,
- The value of R/X ratio in the transmission lines is low.

Accordingly, the linear model of (7) and (8) is respectively as (31) and (32) based on Big-M method and the piecewise linearization approach [6, 31]:

$$-M\times(1-x_{i,j}^{L})\le P_{i,j,m,t,h}^{L}-\left[g_{i,j}\cdot\left(2\cdot V_{i,t,h}-1\right)-\alpha_{i,j,m}\cdot\left(\theta_{i,j,t,h}-\bar{\theta}_{i,j,m,t,h}\right)-\beta_{i,j,m}\left(V_{i,t,h}+V_{j,t,h}-1\right)\right]\le M\times(1-x_{i,j}^{L})\quad \forall i,j,m,t,h \tag{31}$$

$$-M\times(1-x_{i,j}^{L})\le Q_{i,j,m,t,h}^{L}-\left[-b_{i,j}\cdot\left(2\cdot V_{i,t,h}-1\right)+\tilde{\alpha}_{i,j,m}\cdot\left(\theta_{i,j,t,h}-\bar{\theta}_{i,j,m,t,h}\right)+\tilde{\beta}_{i,j,m}\cdot\left(V_{i,t,h}+V_{j,t,h}-1\right)\right]\le M\times(1-x_{i,j}^{L})\quad \forall i,j,m,t,h \tag{32}$$

where M is a large constant that is considered to be 10^6, $\theta_{i,j}$ is equal to $\left(\delta_i-\delta_j\right)$, and the parameters of α , $\tilde{\alpha}$, β and $\tilde{\beta}$ are obtained by the following formula:

$$\alpha_m = \frac{\partial \Phi}{\partial \theta}\Big|\theta = \tilde{\theta}_m,\ \ \tilde{\alpha}_m = \frac{\partial \Psi}{\partial \theta}\Big|\theta = \tilde{\theta}_m \quad \forall \tilde{\theta}_m = m \times \Delta\theta; \forall m \tag{33}$$

$$\beta_m = \Phi\Big|\theta = \tilde{\theta}_m,\ \ \tilde{\beta}_m = \Psi\Big|\theta = \tilde{\theta}_m \quad \forall \tilde{\theta}_m = m \times \Delta\theta; \forall m \tag{34}$$

Note that inequality (9) will be expressed as (35) considering the linearization method of AC power flow constraints in the circular plane. Then, this plane can be converted into a polygon as Fig. 2 where each edge is a linear equation function as $\cos(n\Delta\alpha)P + \sin(n\Delta\alpha)Q = S$ [28]. Therefore, the polygon can be modeled as $\cos(n\Delta\alpha)P + \sin(n\Delta\alpha)Q \leq S$, where $n \in \{1, 2, \ldots, n_n\}$ is the index of circular plane's linearization segments with the total number of n_n, $\Delta\alpha$ is angle deviation that is equal to $360/n_n$. Hence, the linearized model of (35) is written as (36).

$$\sqrt{\left(\sum_m P^L_{i,j,m,t,h}\right)^2 + \left(\sum_m Q^L_{i,j,m,t,h}\right)^2} \leq x^L_{i,j} \cdot \overline{S}^L_{i,j} \quad \forall i,j,t,h \tag{35}$$

$$\cos(n\Delta\alpha) \times \sum_m P^L_{i,j,m,t,h} + \sin(n\Delta\alpha) \times \sum_m Q^L_{i,j,m,t,h} \leq x^L_{i,j} \cdot \overline{S}^L_{i,j} \qquad \forall i,j,t,h,n \tag{36}$$

Finally, the proposed MILP model for the CPSEP is written as follows:

$$\min\ C_p + C_{op} + C_r \tag{37}$$

Subject to:

$$(2)\text{-}(6),\ (10)\text{-}(32),\ (36) \tag{38}$$

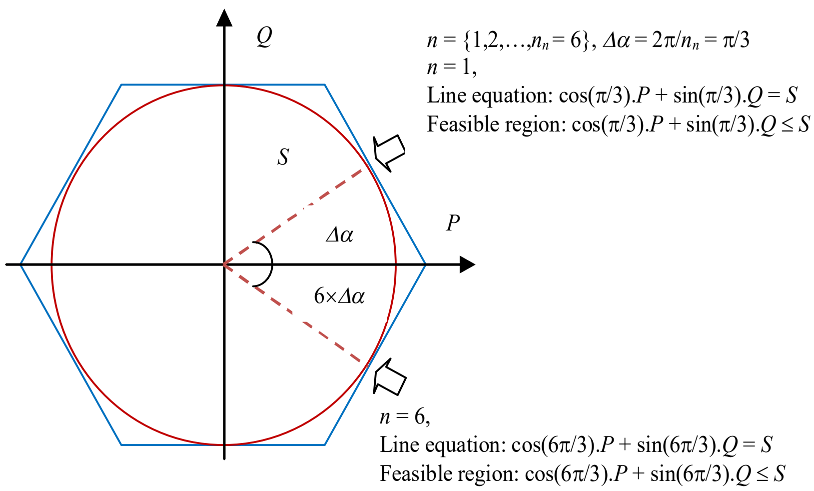

Fig. 2. The proposed linearization method to the circular plane [28].

3. Hybrid Stochastic/Robust CPSEP Model

It is noted that the proposed problem, (37)-(38), includes the uncertainty of load, P^D and Q^D, energy price, ρ, maximum WFs active power, $\overline{P}^W$, and availability/unavailability of the network equipment. Also, it is stated that one of the important indices in the proposed CPSEP method is the reliability index or EENS that is independent from energy price and is highly dependent on the uncertainty of the availability/unavailability of the network equipment. Moreover, it is not highly changed with respect to the uncertainty of load due to the low forecasted load error.

Therefore, the uncertainty of availability/unavailability of the network equipment can be modeled by SBSP using MCS to generate the significant number of scenario samples based on the forced outage rates (FORs) of GUs and transmission lines which follow the Bernoulli probability distribution function [6]. Also, the other uncertain parameters are modeled based on the BURO [28], where its theory has been presented in [28]. In this method, the true value of the uncertain parameter is equal to $(1+\sigma)\times\overline{P}-\delta\times\max\left[\overline{P}\right]$ or $(1-\sigma)\times\overline{P}+\delta\times\max\left[\overline{P}\right]$ in the worst-case scenario according to the objective function and its location, where σ and δ are the adjusting parameters that introduce uncertainty level and feasibility tolerance, respectively. $\overline{P}$ refers to the forecasted value of the uncertain parameter [28].

The first step of the BURO is to reformulate the proposed CPSEP problem as the standard form of this robust method, where the uncertain parameters should be placed in the inequality constraints. Therefore, the standard format of the CPSEP, (37)-(38) can be written as follows:

$$\min\ C_p+C_{op}+C_r \tag{39}$$

Subject to:

Constraints (2), (4), (10)-(13), (15)-(32), (36) (40)

Constraints (10), (12), (13), (15)-(21), (24), (26)-(32), (36) for all scenarios (41)

$$C_o-\text{Right side of Eq.(3)}\geq 0 \tag{42}$$

$$\sum_g A_{Gi,g}\cdot Q^G_{g,t,h}-\sum_j A_{Li,j}\cdot Q^L_{i,j,t,h}\geq\sum_l A_{Di,l}\cdot Q^L_{l,t,h}\quad\forall i,t,h \tag{43}$$

$$\sum_g A_{Gi,g}\cdot P^G_{g,t,h}+\sum_w A_{Wi,w}\cdot P^W_{w,t,h}+\sum_s A_{ESS\,i,s}\cdot\left[P^{dch}_{s,t,h}-P^{ch}_{s,t,h}\right]-\sum_j A_{Li,j}\cdot P^L_{i,j,t,h}+\sum_l A_{Di,l}\cdot P^{DR}_{l,t,h}\geq\sum_l A_{Di,l}\cdot P^D_{l,t,h}\quad\forall i,t,h \tag{44}$$

$$P^W_{w,t,h}-x^W_w\cdot\overline{P}^W_{w,t,h}\leq 0\quad\forall w,t,h \tag{45}$$

$$P^{LNS}_{i,t,h,k}+\left(\text{Left side of Eq.(43) with indices } k \text{ for all powers}\right)\geq\sum_l A_{Di,l}\cdot P^D_{l,t,h}\quad\forall i,t,h,k \tag{46}$$

In the above model, constraints (42)-(44), and (46) are the same as (3), (6), (5), (22) and (23), respectively. Because the equations $a = b$ and $a \geq b$ is the same in the optimization theory of the *minimization* strategy. Finally, the hybrid stochastic/robust optimization with adjusting parameters of uncertainty level (σ) and feasibility tolerance (δ) for the CPSEP problem can be written as follows while index k is removed from the uncertain parameters of load, energy price and maximum WF power:

$$\min\ C_p+C_{op}+C_r \tag{47}$$

Subject to:

$$C_o-\text{Right side of Eq.(3)}-\sigma\sum_{y,h}\rho_{y,h}u_{y,h}\geq 0 \tag{48}$$

$$-f\leq u_{t,h}\leq f \tag{49}$$

$$\forall f=CF\times 365\times\left|\left\{\sum_s\left[P^{ch}_{s,t,h}-P^{dch}_{s,t,h}\right]-\sum_l P^{DR}_{l,t,h}\right\}+\sum_k\pi_k\left\{\sum_s\left[P^{ch}_{s,t,h,k}-P^{dch}_{s,t,h,k}\right]-\sum_l P^{DR}_{l,t,h,k}\right\}\right|$$

$$\text{Left side of Eq.(43)} \geq \sum_{l} A_{Di,l} \cdot \left(P_{l,t,h}^{D} + \sigma\left|P_{l,t,h}^{D}\right|\right) - \delta \max\left[P_{l,t,h}^{D}\right] \qquad \forall i,t,h \tag{50}$$

$$\sum_{g} A_{Gi,g} \cdot Q_{g,t,h}^{G} - \sum_{j} A_{Li,j} \cdot Q_{i,j,t,h}^{L} \geq \sum_{l} A_{Di,l} \cdot \left(Q_{l,t,h}^{D} + \sigma\left|Q_{l,t,h}^{D}\right|\right) - \delta \max\left[Q_{l,t,h}^{D}\right] \quad \forall i,t,h \tag{51}$$

$$P_{w,t,h}^{W} - x_{w}^{W} \cdot \overline{P}_{w,t,h}^{W} - \sigma . x_{w}^{W} \cdot \left|\overline{P}_{w,t,h}^{W}\right| \leq 0 \qquad \forall w,t,h \tag{52}$$

$$-\gamma_{l} \cdot P_{l,t,h}^{D} + \sigma\left|\gamma_{l} . P_{l,t,h}^{D}\right| - \delta . \max\left[P_{l,t,h}^{D}\right] \leq P_{l,t,h}^{DR} \leq \gamma_{l} \cdot P_{l,t,h}^{D} - \sigma\left|\gamma_{l} . P_{l,t,h}^{D}\right| + \delta . \max\left[P_{l,t,h}^{D}\right] \qquad \forall l,t,h \tag{53}$$

$$\left(\text{Left side of Eq.(46)}\right) \geq \sum_{l} A_{Di,l} \cdot \left(P_{l,t,h}^{D} + \sigma\left|P_{l,t,h}^{D}\right|\right) - \delta \max\left[P_{l,t,h}^{D}\right] \quad \forall i,t,h,k \tag{54}$$

$$0 \leq P_{i,t,h,k}^{LNS} \leq \sum_{l} A_{Di,l} \cdot \left(P_{l,t,h}^{D} - \sigma\left|P_{l,t,h}^{D}\right|\right) + \delta \max\left[P_{l,t,h}^{D}\right] \qquad \forall i,t,h,k \tag{55}$$

Constraints (40)-(46) (56)

Note that in the proposed HSRO, problem of (47)-(56) uses BURO to model the uncertainty of load, energy price, RES power, and it is solved for different generated scenarios related to the uncertainty of FOR. Hence, the proposed method implements stochastic and robust programming, simultaneously. The main advantage of the proposed HSRO based on BURO is the simplicity of implementation which results in low calculation time and high accuracy. But, in the other robust model based on the adaptive robust programming, the formulation is more complex with the higher calculation time with respect to BURO [3, 28]. In other words, there are different robust models such as adaptive robust optimization (ARO), BURO and etc. The BURO benefits from simple process. That is, the formulation of the robust models is much more complex using ARO or other available methods in the area, which results in the higher calculation time. Also, since the problem is linear, therefore, the accuracy of the BURO is high [28].

4. Numerical Results and Discussion

In this section, the proposed HSRO model of the CPSEP problem is implemented on the 6-bus and 30-bus IEEE networks in the GAMS software environment, and thus, the simulation results are done by CPLEX solver [32]. The number of linearization segments of AC power flow equations and circular inequality is assumed to be 5 [31] and 45 [28], respectively.

4.1 Case studies

The following case studies are simulated in this paper to evaluate the capabilities of the proposed strategy:

Case A: Coordinated G&TEP

Case B: Coordinated G&TEP considering WF planning

Case C: Coordinated G&TEP including WF planning and DR operation

Case D: Flexible CPSEP without DR operation (Coordinated G&TEP including WF and ESS planning)

Case E: Flexible CPSEP with DR operation

Case F: Flexible-reliable CPSEP

In Cases A-E, there are uncertainties of load, energy price and maximum WF active power; hence, these cases will be solved by the robust model. Therefore, there is only one worst-case scenario, and the equations related to reliability and flexibility indices will be removed from formulation (47)-(56). However, to calculate the system flexibility in these cases, the results of the proposed robust and deterministic CPSEP method should be firstly extracted, and then, the flexibility of the system can be calculated by (26)-(30) while considering $\pi = 1$. In addition, Case F includes all considered uncertain parameters; hence, it is modeled as (47)-(56). Also, 50 scenario samples are generated to model the availability/unavailability of the network equipment by MCS.

4.2 6-bus IEEE network

In this section, the proposed linear CPSEP method is implemented on the modified 6-bus IEEE network presented in [6], where different characteristics, i.e., location, operation cost, investment cost, capacity, resistance, reactance, and FOR, of the existing and candidate transmission lines and GUs as well as WF are available in [2, 6]. Moreover, it is assumed that there are 30%, 30% and 40% of the total network load with power factor 0.9 lag in the buses 3-5, respectively. Also, the daily load factor curve is shown in [28] and the yearly load factor for years 1-10 are respectively 0.95, 0.961, 0.972, 0.983, 0.994, 1.005, 1.016, 1.027, 1.039, and 1.05 with assuming coincidence factor to be 0.7. The base power and voltage in this network are 100 MVA and 230 kV, and the allowable range of voltage is [0.95 1.05] p.u.. Moreover, the daily power percentage and energy price curves are obtained from [33] and [28], respectively. The VOLL is considered to be 1000 $/MWh [6], and load participation rate in the DRP is 0.30 [2]. In addition, three ESSs are planned in this network, where they have 88% charging/discharging efficiency, 5 MW maximum active power, 2 MW and 20 MW minimum and maximum stored energy, respectively. Also, the investment cost is 20 $/kWh/year.

- *Complexity of model and solution methodologies:* Table 2 reports the convergence results of the proposed scheme in case F for load level 60 MW and different models. In the deterministic model (there are no uncertainty and forecasting error), the convergence of the mixed integer non-linear programming (MINLP) and mixed integer linear programming (MILP) formulations is investigated. Based on this table, solvers of MINLP model (BARON, BONMIN, DICOPT and KNITRO [32]) cannot obtain a unique optimal solution. Also, DICOPT and KNITRO are not able to achieve a feasible solution, and the objective function value is not same as BARON and BONMIN while the total number of variables (equations) is same for these solvers. But it is not the issue for MILP model while its solvers (BONMIN, CBC and CPLEX [32]) obtain a unique optimal solution at low calculation time in comparison with MINLP model. Noted that, the total number of variables (equations) in MILP is more than MINLP. Among these solvers, CPLEX has superior solution results with respect to other solvers while it finds the solution at the least calculation time. In addition, the convergence results of the hybrid stochastic-robust optimization model using different robust models, i.e., BURO, adaptive robust optimization (ARO) [3, 8] and information-gap decision theory (IGDT) [34], for uncertainty level of 0.1 have been addressed in Table 2. Noted that, IGDT generally obtains the maximum value of the uncertainty level. As seen in Table 2, the objective function values are close in the robust models, while, BURO has the least calculation time. Because the total number of equations and variables for BURO is lower than others. As inferred from the results, the proposed MILP model using BURO has the most satisfactory solution from the viewpoint of model complexity.

Table 2. Results of the complexities in the different models for the load level 60 MW in Case F.

Deterministic model						
Model	Solver	Total number of equations	Total number of variables	Objective function	Calculation time (s)	Solution state
MINLP	BARON	9472	56121	103.7	2695.3	Feasible
	BONMIN	9472	56121	97.6	1247.5	Feasible
	DISOPT	9472	56121	-	-	Infeasible
	KNITRO	9472	56121	-	-	Infeasible
MILP	BONMIN	12739	68428	90.9	104.7	Feasible
	CBC	12739	68428	90.9	95.2	Feasible
	CPLEX	12739	68428	90.9	81.4	Feasible

Hybrid stochastic-robust model					
Robust model	Total number of equations	Total number of variables	Objective function	Calculation time (s)	Solution state
BURO	13933	68428	112	98.4	Feasible
ARO	16893	73483	112.1	134.2	Feasible
IGDT	14078	68428	111.8	107.3	Feasible

– *Uncertainty parameter in the robust model*: Firstly, the true values of the active and reactive load, energy price and maximum active power of WF for cases A-F in the worst-case scenario are presented in Table 3. This table shows the results of the robust model for the sixth year of the planning period based on the peak load (60 MW) and different adjusting parameters of model, i.e., δ and σ. According to this table, it is observed that in the worst-case scenario, if the level of uncertainty (σ) is increased compared to the corresponding deterministic model of load scenario (δ and $\sigma = 0$), the rate of active and reactive load increases and the maximum generation capacity of WF is decreased. However, the decline or rise in energy prices depends on the type of the case study such that in Case C (that includes DRPs and ignores ESS) the price has been reduced by increasing σ, because the coefficient of the DRP operation cost is negative in the objective function (47) according to (48). Thus, the energy price should be reduced in the worst-case scenario to decrease the DRP benefit in the robust model. But it will be increased by increasing σ in Case D that includes only ESS as the flexible source, because the coefficient of the ESS operation cost is positive in the objective function. In Cases E and F, the DRP impact has overcome with the ESS impact; hence, the value of the energy price will be increased if the uncertainty level increases. Finally, it is noted that the results of the robust model by increasing δ in the worst-case scenario in comparison with the deterministic model in Cases A-E or stochastic model in Case F are not in the same direction as a result of increasing σ.

Table 3. The true values of uncertain parameters for the load level of 60 MW in the sixth year of planning in different cases.

Uncertain parameter	Total daily active load (MW)		
δ and σ	0 & 0	0.01 & 0	0 & 0.1
Case A-F	914	905	1005
Uncertain parameter	Total daily reactive load (MW)		
δ and σ	0 & 0	0.01 & 0	0 & 0.1
Case A-F	442.5	438	487
Uncertain parameter	Daily energy price ($/MWh)		
δ and σ	0 & 0	0.01 & 0	0 & 0.1
Case A-B	-	-	-
Case C	550	555.5	495
Case D	550	544.5	605
Case E	550	551.3	523.4
Case F	550	551.3	523.4
Uncertain parameter	Daily total $\bar{P}^{w}$ (MW)		
δ and σ	0 & 0	0.01 & 0	0 & 0.1
Case A	-	-	-
Case B-E	79.2	80	71.3
Case F	79.2	100	89.1

– *Economic results*: Table 4 presents the investment, operation and reliability costs of the proposed CPSEP in all cases for different load levels and adjusting parameters of the robust model. Accordingly, there are some considerations which are inferred from this table as follows:

Table 4. The costs in the proposed scheme for different load levels in all case studies and robust models.

Cost (M$)		Planning and operation/Reliability		
δ and σ		0 & 0	0.01 & 0	0 & 0.1
Load level=20 MW	Case A	19.5/-	19.3/-	21.5/-
	Case B	18.5/-	18.3/-	20.3/-
	Case C	17.7/-	17.5/-	19.5/-
	Case D	18.5/-	18.3/-	20.3/-
	Case E	17.7/-	17.5/-	19.5/-
	Case F	20.1/1.2	19.8/0.9	23.3/1.7
Cost (M$)		Planning and operation/Reliability		
δ and σ		0 & 0	0.01 & 0	0 & 0.1
Load level=40 MW	Case A	44.8/-	44.5/-	54/-
	Case B	42.3/-	41.9/-	50.3/-
	Case C	37.3/-	36.9/-	43.2/-
	Case D	42.3/-	41.9/-	50.3/-
	Case E	37.3/-	36.9/-	43.2/-
	Case F	46/4.7	45.4/4.2	57.5/6.1
Cost (M$)		Planning and operation/Reliability		
δ and σ		0 & 0	0.01 & 0	0 & 0.1
Load level=60 MW	Case A	81.1/-	80.2/-	98.3/-
	Case B	76.8/-	77.9/-	89.2/-
	Case C	66.1/-	65.3/-	76.5/-
	Case D	70.4/-	69.6/-	81.5/-
	Case E	62.3/-	61.5/-	74.3/-
	Case F	83.3/8.8	82.5/8.2	101.4/10.6
Cost (M$)		Planning and operation		
δ and σ		0 & 0	0.01 & 0	0 & 0.1
Load level=80 MW	Case A	116.3/-	115.1/-	132.4/-
	Case B	113.4/-	112.2/-	127.3/-
	Case C	100.1/-	99.1/-	115.2/-
	Case D	105.4/-	104.4/-	121.3/-
	Case E	96.6/-	95.5/-	109/6/-
	Case F	121.3/11.4	120.1/10.8	138.7/13.2

– The reliability cost will be increased if the load level is increased, because the load not supplied and EENS will be increased in this condition.

– Increasing the load level in all cases causes an increase in the investment and operation costs due to the increasing number of equipment and energy demand in this condition.

– By increasing the uncertainty level, the cost of the proposed scheme increases due to increasing/decreasing load/WF capacity in the worst-case scenario which highlights the need for more equipment in this condition and consequently the increased cost of energy and power outages. However, the results of increasing δ is in the opposite direction of increasing σ.

– For different load levels and robust models, Case E has the least cost with respect to the other cases, but the cost value in the Case F is the highest. Accordingly, it can be inferred that the G&TEP cost is low in the presence of local sources such as WF, ESS and DRP, and also, improving the system reliability needs a high cost due to the increasing equipment number in the expanded network.

– *Investigating network indices*: The indices of the technical performance, flexibility and peak load carrying capability (PLCC) of the network in different robust models are depicted in Fig. 3. This figure shows the network technical indices such as maximum voltage deviation and energy loss for the load level of 60 MW in different robust models, RO(σ, δ). As shown in Fig. 3, the cases E and A respectively have the minimum and maximum voltage deviation and energy loss as results of the benefits of local sources, ESSs and active loads operation in G&TEP. In addition, variations of σ/δ have small impacts on the changes of voltage deviation and energy loss for cases E and F in the robust model in comparison with the results of the deterministic model.

Figs. 4 and 5 show respectively the PLCC and system flexibility curves in the different robust/HSRO models and cases. It is noted that in comparison with the deterministic model of the cases A to E and the stochastic model of case F ($\delta = \sigma = 0$), it can be concluded that the local sources, ESSs and active loads in the G&TEP problem can increase the PLCC based on the results of Case E with respect to Case A. Also, adding fast-flexible sources such as ESS and DRP to CPSEP in Case E can obtain the higher flexibility level in the network versus Case B (Fig. 5). Moreover, the difference of these indices between cases E and F (considering reliability equations) is low that indicates the proposed method can acquire high reliability, flexibility and PLCC, together with the low voltage deviation and energy loss with the rational cost, as shown in Table 4. Finally, increasing the uncertainty level/feasibility tolerance in the robust model or hybrid stochastic/robust model causes that the PLCC and system flexibility to be increased/decreased due to reducing/increasing the feasibility space of the proposed problem in this condition.

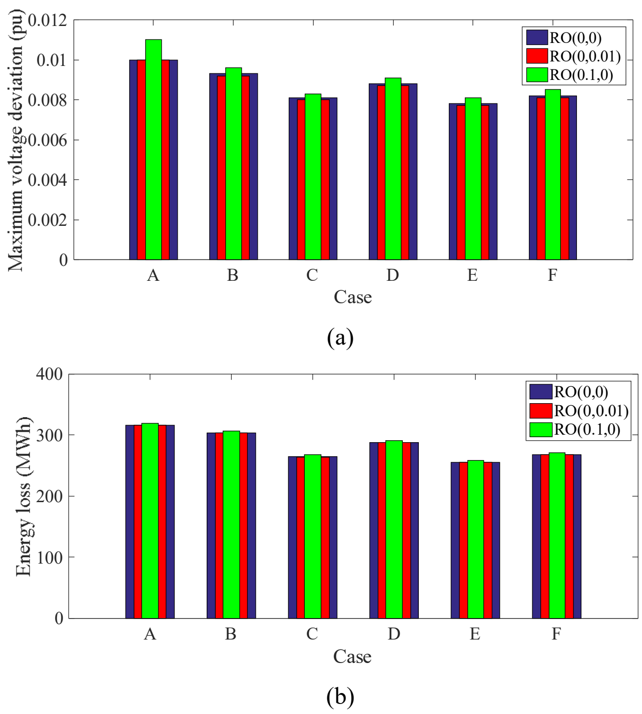

Fig. 3. Technical network indices, (a) maximum voltage deviation, (b) energy loss for the load of 60 MW, in robust/HSRO models of all cases.

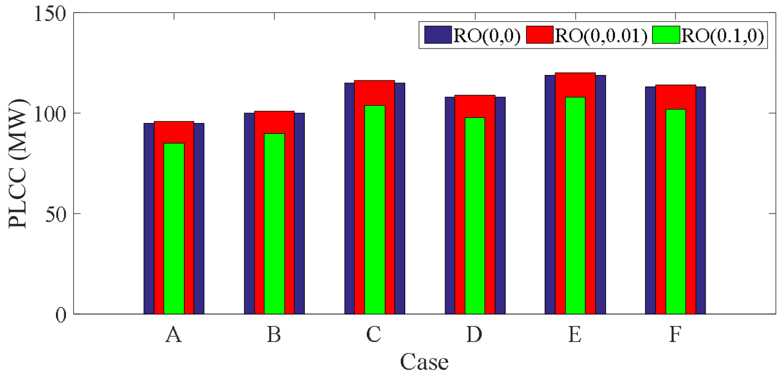

Fig. 4. The PLCC value in all cases and robust models, RO(σ, δ).

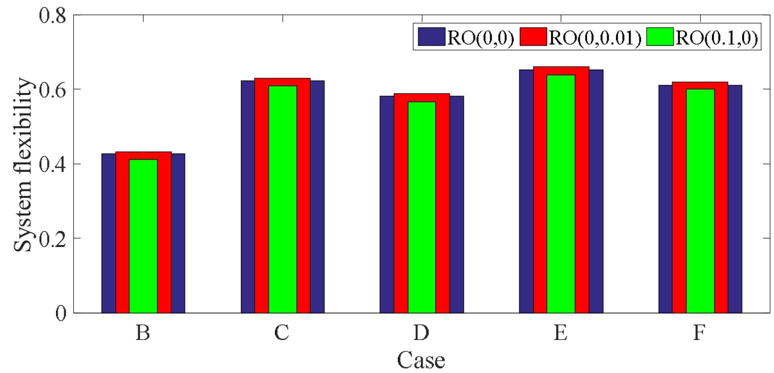

Fig. 5. System flexibility for the load level 60 MW in all cases of robust models, RO(σ, δ).

4.3 30-bus IEEE network

In this section, the proposed strategy is simulated on the 30-bus IEEE network, where the data of GUs, WFs, transmission lines and load is addressed in [35]. The other data such as daily load factor, energy price, WF power percentage curves, load participation rate and other parameters is similar to the 6-bus IEEE network data. Also, ESS can be connected to each bus, and in this network, 8 ESSs are considered. In Fig. 6, the daily DRP power curve in Case E at last year of planning considering the peak load of 400 MW has been illustrated for different robust models. In this figure, the positive/negative values mean the load power is reducing/increasing. As seen, all consumers reduce their load at high energy price hours, 14:00-22:00, and they increase their consumption at a low energy price period, 1:00-13:00 and 23:00-24:00. Therefore, DRP reduces the cost of the proposed strategy by shifting the load at peak load times to off-peak load hours. In addition, the DRP power will increase, if the uncertainty level is increased to satisfy the power balance constraint in the power system. But if the feasibility tolerance is increased then it would be reduced to satisfy this constraint. Fig. 7 depicts the daily energy curve of ESS in the last year of planning for Case E with the load level of 400 MW. In this figure, increasing/decreasing energy means charging/discharging modes of the ESS. As seen in Fig. 7, the ESS is charged in the period of low energy price, 1:00-7:00, and discharged at the period of 18:00-22:00 that is related to high energy price. Therefore, as the DRP and ESS reduce the cost of the CPSEP method, they will increase/decrease their power with increasing σ/δ to satisfy the power balance constraint.

Fig. 8 provides data about the reliability cost and the sum of investment and operation cost versus VOLL for different robust models. Accordingly, increasing the penalty price of VOLL causes decreasing reliability cost and increasing operation and planning costs for all hybrid stochastic/robust models; hence, this cost is rational for reducing the EENS. In addition, increasing the σ or δ increases/decreases different costs, but it can reduce the EENS in the worst-case scenario by considering enough extra costs.

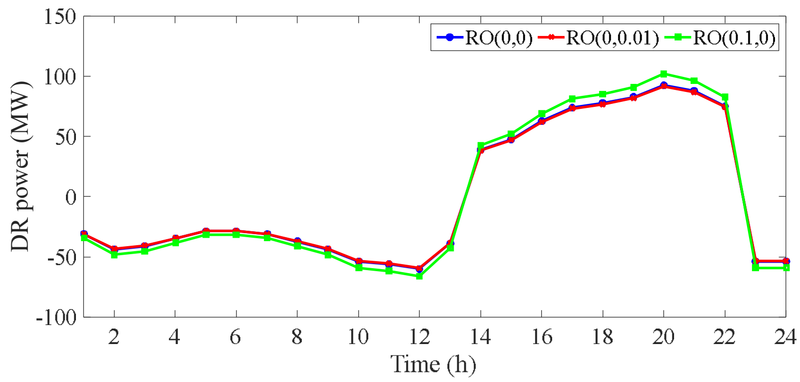

Fig. 6. Daily power curve DRPs for case E at the load level of 400 MW in the last year of planning in different robust models, RO(σ, δ).

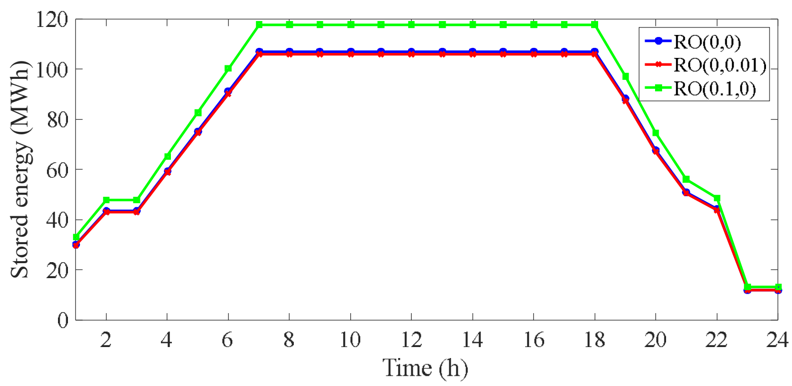

Fig. 7. Daily energy curve of ESSs for Case E at the load level of 400 MW in the last year of planning in different robust models, RO(σ, δ).

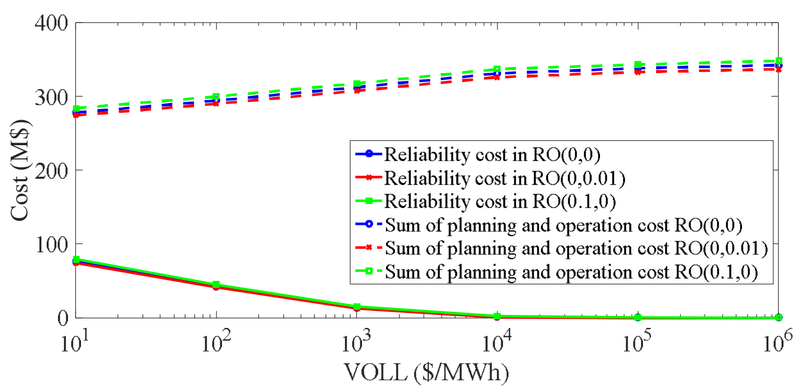

Fig. 8. The cost variations versus VOLL in case F at the load level of 400 MW in different robust models, RO(σ, δ).

5. Conclusion

In this paper, a hybrid stochastic/robust CPSEP strategy has been presented to perform the expansion planning of the transmission lines, generation units, wind farms and energy storage systems in a power system considering the incentive-based demand response programs. The proposed method minimizes the sum of investment, operation, and reliability costs subject to AC optimal power flow constraints in the presence of different local sources, storages, and active loads. The original model of this strategy is in the form of MINLP, where in this paper it was converted to the MILP counterpart by means of linearization methods to obtain a globally optimal solution with low calculation time and error. Also, BURO has been used to model the uncertainty of load, energy price and maximum active power output of WF, and the SBSP has been used to model the uncertainty of availability/unavailability of the network equipment in this paper. Finally, according to the numerical results, it is concluded that the proposed strategy can provide a reliable and flexible power system operation and planning including low energy loss and voltage deviation via optimal planning and scheduling of the network equipment, local sources, storages, and active loads. Noted that in the CPSEP problem, different indices such as security, emissions, cost, and operation are important to achieve a more secure and robust expanded network. While improving one index has no guarantee of improving another. Thus, to cope with this issue, the future studies in this area can focus on developing multi-objective CPSEP model based on decomposition techniques.

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